Exploratory Data Analysis

Lecture 10

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Recap Hypothesis Testing

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   $H_0 : \beta_k = 0$
   $H_A : \beta_k \neq 0$

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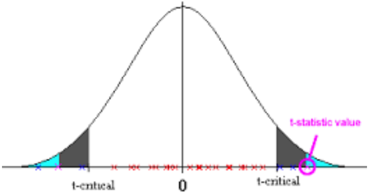

p-values

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In other words:

p-value is the probability that you rejected a H_0 that was correct (assuming that the estimate is in the expected direction).

Graphically, it's two times the area under the curve of the t-distribution between $|t_k|$ and ∞.

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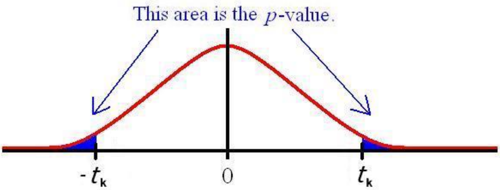

p-value Rule of Thumb

To cofidently reject a null, you will want a low p-value

Rule of Thumb:

$p - value < 0.05 \rightarrow$ reject H_0

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Regression Results

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                            OLS Regression Results
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Dep. Variable:                 Profit   R-squared (uncentered):                  0.984
Model:                            OLS   Adj. R-squared (uncentered):             0.982
Method:                 Least Squares   F-statistic:                             839.8
Date:                Wed, 29 Sep 2021   Prob (F-statistic):                   2.95e-49
Time:                        11:27:08   Log-Likelihood:                        -661.85
No. Observations:                  60   AIC:                                     1332.
Df Residuals:                      56   BIC:                                     1340.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
RD             0.7145      0.068     10.490      0.000       0.578       0.851
Admin          0.2546      0.043      5.927      0.000       0.169       0.341
Marketing      0.0962      0.025      3.915      0.000       0.047       0.145
Office         0.9425      0.663      1.421      0.161      -0.386       2.271
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Omnibus:                        6.429   Durbin-Watson:                   1.745
Prob(Omnibus):                  0.040   Jarque-Bera (JB):                9.643
Skew:                          -0.196   Prob(JB):                      0.00805
Kurtosis:                       4.924   Cond. No.                         91.1
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Although R^2 and $\bar{R}^2$ measure the overall degree of fit of an equation, they don't provide a formal hypothesis test of that overall fit.

But we have the F-test!

The F-test is a joint hypothesis test.

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1. Translate the null hypothesis into constraints on the equation. $\rightarrow$
   Constrained equation: $Y_i = \beta_0 + \epsilon_i$
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2. Estimate the constrained equation and the unconstrained equation to compute:

$$F = \frac{(RSS_M - RSS)/M}{RSS/(N - K - 1)}$$

   where,
   M - degrees of freedom in numerator (nb. of constraints)
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3. Reject H_0 if $F > F_c$
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OLS Assumptions

Notation	Meaning
1. $E(u_i) = 0$	Average value of residuals is zero
2. $Var(u_i) = \sigma^2$	The variance of the residuals is constant
3. $Cov(u_i, x_i) = 0$	There is no linear relationship between residues and x
4. $u_i \sim N(0, \sigma^2)$	Residuals have a normal distribution
5. $Cov(u_i, u_j) = 0$	Residuals don't depend on each other
6. Multicollinearity	Independent variables are not correlated with each other

Model Specification

Specifying an econometric equation consists of three parts:

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Omitting an Important Variable

Omitted Variable Bias

True Model

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon_i$$

Specified Model

$$Y_i = \beta_0^* + \beta_1^* X_{1i} + \epsilon_i^*$$

$$\downarrow$$

$$\epsilon_i^* = \epsilon_i + \beta_2 X_{2i}$$

If X_1 and X_2 are correlated Cov $(X_{1i}, \epsilon^*) \neq 0 \rightarrow \underbrace{\hat{\beta}_1^* \neq \beta_1}_{\text{Biased!}}$

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$\hat{\beta}_1^* = \beta_1$ but Var $(\hat{\beta}_1) \uparrow$ thus $\underbrace{t_{X_1} \downarrow}_{\text{Biased!}}$

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Specification Criteria

1. Theory: Is the variables place in the equation unambiguous and theoretically sound?
2. t-Test: Is the variables estimated coefficient significant in the expected direction?
3. $\bar{R}^2$: Does the overall fit of the equation (adjusted for degrees of freedom) improve when the variable is added to the equation?
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Choosing the Functional Form

Should we include the intercept β_0?

- Beginner researchers may want to supress the intercept when there is no logical interpretation for β_0.
- This would be a mistake. β_0 should be suppressed only on very rare occasions.

  For example: $C_i = \beta_0 + \beta_1 Q_i + \epsilon_i$

  where,

  C_i are the fixed and variable costs of businesses in a branch
- Excluding β_0 in this context would preserve one degree of freedom and would supposedly make the estimate of β_1 more accurate.
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Choosing the Functional Form

Should we include the intercept β_0?

- Beginner researchers may want to supress the intercept when there is no logical interpretation for β_0.
- This would be a mistake. β_0 should be suppressed only on very rare occasions.

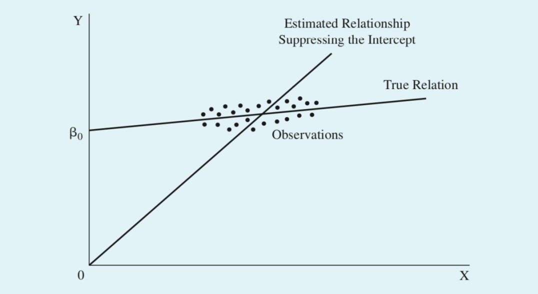
  For example: $C_i = \beta_0 + \beta_1 Q_i + \epsilon_i$

  where,

  C_i are the fixed and variable costs of businesses in a branch
- Excluding β_0 in this context would preserve one degree of freedom and would supposedly make the estimate of β_1 more accurate.
- However such examples in real life are rare!
- The risks associated with supressing β_0 most times outweight the benefits of doing so.

Suppressing β_0

By omitting the constant term, we force the impact of the constant into the estimates of the other coefficients.



- The estimated regression will go through the origin
- $\hat{\beta}_1 \neq \beta_1$ - biassed coefficient
- t-scores $\uparrow$ - also biased

General Advice: Do Not Suppress the Intercept

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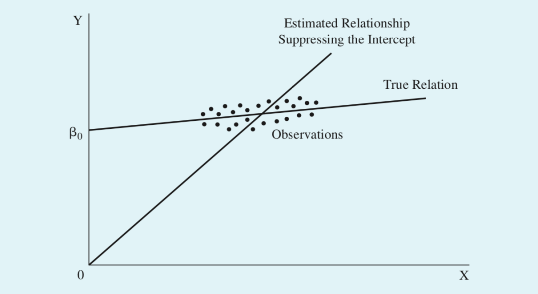

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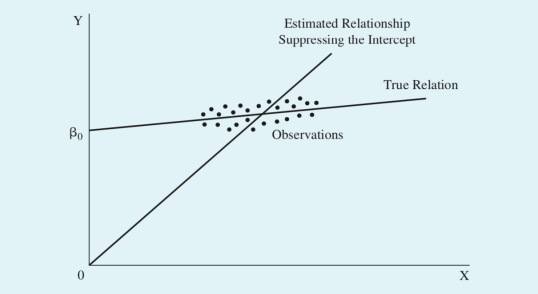

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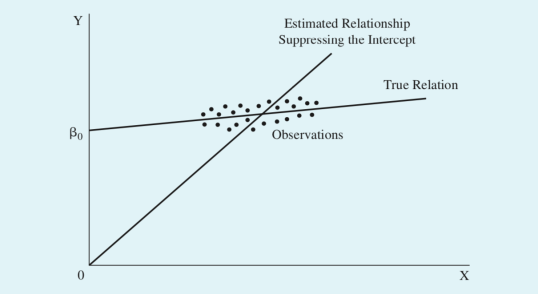

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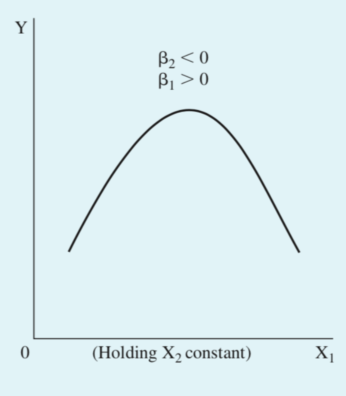
Polinomial Regressions

Sometimes the relationship between X and Y cannot be explained by a line.

Relationship between Earnings and Age.

- As a young worker gets older, his or her earnings will increase.
- Beyond some point an increase in age will not increase earnings, and around retirement earnings will start to fall abruptly with age.

Relationship between Earnings and Age



$$\text{Earnings}_i = \beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Age}_i^2 + \cdots + \epsilon_i \qquad \frac{\Delta Y}{\Delta X_1} = \beta_1 + 2\beta_2 X_1$$

General Advice: Rely of Theory when Defining the Functional Form of Your Model.

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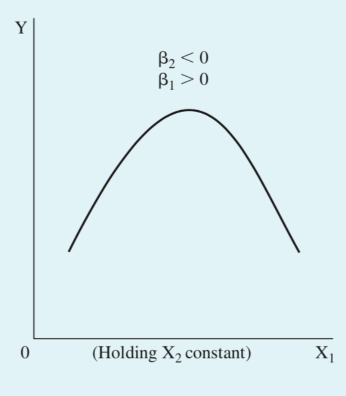

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Choosing the correct form of the stochastic error term

1. Multicollinearity
2. Serial Correlation $Cov(u_i, u_j) \neq 0$
3. Heteroskedasticity $Var(u_i) \neq \sigma^2$

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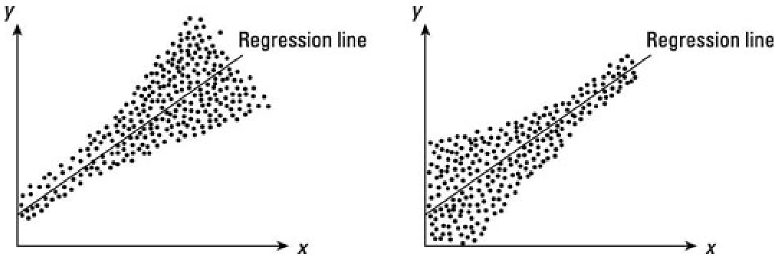

Let's get Started!

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